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A Study on Demand Relationship Extraction of Automobile Users Based on Two-Channel Fusion

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Abstract. Using user review data from the Sina Automobile Complaints Platform, the article study focuses on relationship extraction in the automobile product domain based on the entities of automobile users' needs that have been identified in previous studies. Existing studies are ineffective in solving the problem of multiple meanings of words and dealing with complex relationships between multiple entities, and a single Convolutional Neural Network (CNN) or Bidirectional Long and Short-Term Memory Network (BILSTM) makes it difficult to extract sentence features comprehensively. Therefore, the article proposes a two-channel relational extraction model BERT+ (CNN+BILSTM+ATT, BILSTM+ATT). The innovations of this study are as follows: first, the BERT model is used in the embedding layer to generate the word vectors of the input text sequence; second, the feature extraction layer combines the advantages of two neural networks, CNN and BILSTM, to perform the feature extraction separately; and finally, the feature fusion layer fuses the features of the two-channel outputs to extract the vocabulary and character information fully. Different from the existing method of directly splicing the outputs of the two channels, the model innovatively introduces a fusion algorithm in the feature fusion layer, which uses trainable weight vectors to determine the proportion of the output vectors of the two channels so as to train the optimal ratio and give full play to the advantages of the two neural networks to achieve a better effect of relationship extraction. Finally, the final result is obtained by classifying through a classifier in the output layer. The experimental results show that the F1 value of the model proposed in this paper reaches 92.57%, with the best recognition effect, which verifies the effectiveness of the model in the relationship extraction of automobile user requirements and provides technical support and methodological guarantee for automobile enterprises to obtain knowledge of user requirements and carry out product innovation.

Keywords: Relational Extraction; Feature Fusion; BERT; CNN; BILSTM.
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1 INTRODUCTION

In recent years, with the rapid development of the Internet, people are more and more willing to express their views and opinions on the Internet, and there is a rapid increase in the number of texts on the Internet about various fields, which contain a large amount of knowledge that can be utilized for exploitation [1]. The article utilizes the user comments of the Sina Auto Complaints Platform in the previous study to obtain the corresponding entity data and performs entity-relationship extraction to obtain the corresponding entity-relationship-entity triples.

Relation Extraction (RE) is one of the key techniques in the field of natural language processing, and it is an indispensable step in building a knowledge graph [2]. As a subtask of information extraction, after entity extraction, relationship extraction is needed to get entity-relationship-entity ternary [3]. Relationship extraction requires predefining the relationship types and then extracting the defined entity relationships from the unstructured text.

According to the structure of the model and whether the entity is marked in the text [4], the relationship extraction methods can be categorized into Pipeline methods [5] and Joint extraction [6]. Joint extraction is a pipeline extraction method because the article uses already labeled entity data. The joint extraction method is able to accomplish both tasks of named entity recognition and relationship extraction simultaneously, and both tasks use the extraction model of shared parameters and joint decoding. Wei et al. [7] proposed a new cascaded binary labeling framework (CasRel) that models relations as functions that map subjects to objects in a sentence, improving the performance of the model. Wang et al. [8] proposed a single-stage joint extraction model, TPLinker, which is capable of discovering overlapping relationships that share one or two entities while being independent of exposure bias, effectively solving the exposure bias problem. Zhang et al. [9] proposed encoder-decoder-based generation introducing a single shared converter module for joint extraction of contrast information using generative converters. Zhao et al. [10] proposed an actively supervised clustering called OpenRE with simultaneous cluster learning and relation labeling. Luo et al. [11] inspired by the tree-like relationship structure in medical texts, proposed a bidirectional tree labeling model BiTT, which forms medical relationship triples into two binary trees and converts the trees into a sequence of word-level labels. Relationship extraction methods can be categorized into relationship classification problems under supervised conditions based on the characteristics of the data used in the study [12-14], the relationship classification problem under supervised conditions, the relationship classification problem under small samples [15-16] and relationship classification problems under remote supervision [17-18]. This paper belongs to relational extraction with small samples. Relational extraction methods can be categorized into Sentence-level relational extraction and Document-level relational extraction according to the size of the extracted dataset [19]. Relationship extraction methods are similar to named entity recognition methods [20-21]. They can be classified into the following categories in terms of time: Early lexicon rule-based approaches [22] need to manually design and specify the predefined template rules, so as to match the text and the predefined template to obtain the relationship category, although there is no need for training data, easy to interpret and the use of a wider range of advantages, but there is also the need for time and professional knowledge to design the rules of different domains and the construction of a long period of time. Kernel function-based approach [23]. The syntactic structure of the text is preserved intact, and it can maximize the use of the relevant information contained in the text, and the relationship distance is calculated by the similarity of the structure without the need to construct feature vectors. Although this method does not require many rules and features, the structure formed due to the different semantic representations has an impact on the experimental results. Based on statistical machine learning [24], the relationship instances are represented as feature vectors in a high-dimensional space, and the performance of the model is very much dependent on the merit of the feature selection. Deep learning-based methods [25] typically rely on a distributed representation of words and characters to learn sentence or sequence features through an end-to-end training process. In the field of relational extraction, common deep learning models include Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) as a variant of

RNN. Memory (LSTM) and Gated Recurrent Neural Network (GRU) as variants of RNN. Among them, LSTM and GRU have become the focus of relational extraction research because they lift the limitations of RNNs in dealing with problems such as long-term dependencies and gradient vanishing. Deep learning models have strong robustness and generalization capabilities, can automatically learn feature representations, and do not need to manually define features, which reduces the model's dependence on domain knowledge and can make full use of contextual information to improve the accuracy of relationship extraction, and thus become the mainstream approach in relationship extraction tasks [26]. Therefore, it has become the mainstream method in the task of relationship extraction.

2 RELATED WORK

Relational extraction is an indispensable step in acquiring textual knowledge and is a research hotspot in the field of Artificial Intelligence, deep learning-based methods have been applied to many fields and achieved many research results—stable Wang et al. [27] proposed a relationship extraction model PCNN-EFMA that integrates entity features and multiple types of attention mechanisms, which solves the problems of poor domain specificity and insufficient utilization of domain entity feature information in remote supervised relationship extraction methods. Xia Yikun et al. [28] proposed a fusion model combined with relationship enhancement for opinion relationship extraction, which solves the problems of overlapping relationships and the inability of a single model to fully recognize all triples in the task of opinion information relationship extraction. Han et al. [29] proposed a relationship extraction model that utilizes the co-occurrence correlation of relationships to solve the long-tail and multi-label problems of the document-level relationship extraction task. Li et al. [30] proposed a Relation-aware (RA) embedding mechanism for relational extraction, which effectively improves the performance of relational extraction by utilizing the attention mechanism to distinguish the importance of different relational labels for each word of a sentence, thus integrating the relational label information into the sentence embedding. Sun et al. [31] proposed a relationship extraction model Knowledge Guided Attention and Graph Convolutional Network (KGAGN) for extracting chemical-disease relationships, using Bio-BERT and ELMo as embedding models, and combining dependency trees and GCN, which effectively improves the model performance. Li et al. [32] proposed an effective document-level relationship extraction model that utilizes Gaussian probability distribution to calculate the weights of co-occurring sentences and their neighboring entity sentences and combines with the self-attention mechanism, which effectively improves the performance of relationship extraction for extracting chemically induced diseases from biomedical articles. Xiao et al. [33] proposed a hybrid attention-based Transformer module that utilizes multi-head self-attention to capture word-level syntactic information, effectively solving the mislabeling problem associated with remote supervised learning. Zhang et al. [34] proposed a relationship extraction method that combines text with a densely connected graph convolutional network (DCGCN) by forming different weight matrices through the mechanism of multi-head attention to extract deeper structural information in text, which effectively improves the performance of extracting overlapping relationships. Zhang et al. [35] proposed a graph structure-based entity-relationship extraction model RoGCN-ATT, which uses RoBERTa-wwm-ext-large Chinese pre-trained model as a sequence encoder and solves the problem of the inadequacy of the existing entity-relationship extraction methods in dealing with non-Euclidean data. Wen et al. [36] proposed a biomedical relationship extraction method based on cue learning, adding an annotation label for entities to cue entities for the purpose of entity semantic enhancement as well as linking contextual information.

Although many scholars have achieved significant results in optimizing and improving the relationship extraction model based on deep learning. However, there are relatively few studies related to relationship extraction in the field of automotive products, and none of the existing methods can well solve the problem of multiple meanings of the word, and do not have a good recognition effect when facing complex interrelationships between multiple entities [37]. In the face of complex interrelationships between multiple entities, the recognition effect is not good.

Aiming at these problems, innovations are made with an eye to relationship extraction methods in the automotive domain, and since hybrid models have better performance in text categorization compared to single models [38] As a result, a single convolutional neural network or BILSTM network can not extract all the features of the sentence well, so a two-channel fusion relationship extraction model BERT+(CNN+BILSTM+ATT, BILSTM+ATT) is proposed, which combines the advantages of the two neural networks in the feature extraction layer to carry out the feature extraction, and fuses the output of the feature from the two channels in the feature fusion layer. In the feature fusion layer, the output features of the two channels are fused to obtain the features that fully integrate vocabulary and character information extraction. Moreover, unlike the existing method of directly splicing the outputs of the two channels, the model innovatively proposes a fusion algorithm in the feature fusion layer, which uses a trainable weight vector to determine the ratio of the output vectors of the two channels so as to get the best ratio, thus maximizing the advantages of the two neural networks to achieve a better effect of relationship extraction.

3 DUAL-CHANNEL BASED DEMAND RELATIONSHIP EXTRACTION MODEL FOR AUTOMOBILE USERS

In order to improve the efficiency of the relationship extraction for automobile users' demand, this paper combines the previous research and innovatively proposes a two-channel fusion relationship extraction model BERT+(CNN+BILSTM+ATT, BILSTM+ATT), on the basis of the pre-training model BERT network, the textual features are extracted based on the vocabulary information through CNN+BILSTM+ATT, and the textual features are extracted based on the character information through BILSTM+ATT to extract text features based on character information, after that the two features are fused to get the fused vocabulary and character information extracted features, and then finally do the classification and output the final result through softmax function. The model consists of five parts: embedding layer, feature extraction layer, attention layer, feature fusion layer, and output layer. The model structure is shown in Figure 1.

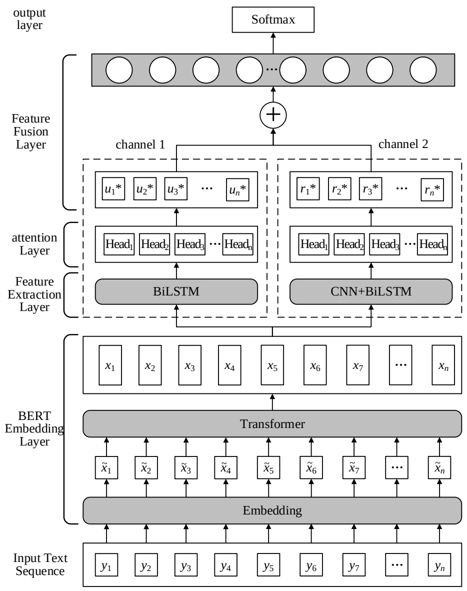

Figure 1: BERT+(CNN+BILSTM+ATT, BILSTM+ATT) dual-channel automotive user demand relationship extraction model.

3.1 Embedding Layer

The input text $S=\{y_1,y_2,y_3\cdots,y_n\}$, n is the length of the word sequence, and the dynamic word vectors of the text sequence are generated using the BERT pre-training model. The word sequence is encoded using the BERT Chinese mapping table, and the [CLS] sentence-initial vector and [SEP] sentence-medial and sentence-end vectors are added to the first part of the text, and the three embedding vectors, i.e., the word vector (token embedding), the segment embedding and the position embedding, which are summed up to obtain the final input sequence representation of the BERT model. The text input sequence $\tilde{X}=\{\tilde{x}_1,\tilde{x}_2\cdots\cdots,\tilde{x}_n\}$ obtained by summing the word vector (token embedding), paragraph vector (segment embedding) and position vector (position embedding) is used as the final input sequence representation of the BERT model. After $\tilde{X}$ is encoded by a multi-layer bidirectional Transformer, the output word vector sequence of BERT model $X=\{x_1,x_2\cdots\cdots,x_n\}$ is obtained, where $X\in\mathbb{R}^{n\times d}$ and d denote the vector dimensions.

The BERT model is different from traditional language models in that it adopts a very special approach; instead of predicting the current word given the previous words, it randomly masks some words and uses all the unmasked words for prediction. The BERT model combines the advantages of OpenAI GPT and ELMO's bi-directional coding, which is a brand-new model. The BERT models are classified into BERTBASE and BERTLARGE according to the parameter sizes. BERTBASE has a smaller number of parameters, and the training and inference speed is usually faster than BERTLARGE for processing small and medium-sized text data sets. Unlike BERTBASE and BERTLARGE, BERTBASE has a smaller number of parameters, and the speed of training and inference is usually faster than BERTLARGE, which is more advantageous for processing small and medium-sized textual datasets. BERT-base is usually good enough to perform well, so in this paper, we choose BERTBASE as the word embedding model, which contains a multi-layer bi-directional Transformer encoder, as shown in Figure 2.

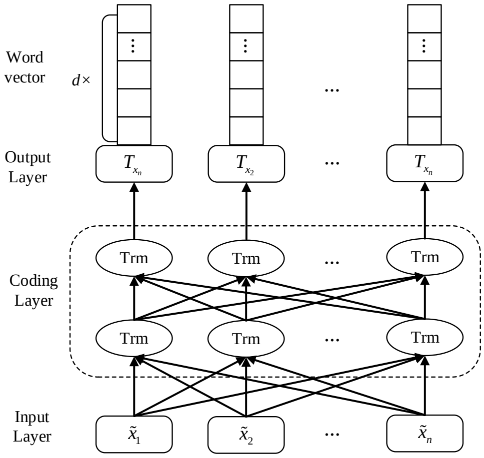

Figure 2: Structure of BERT model network.

3.2 Feature Extraction Layer

Due to the face of unstructured car review text data, the extraction effect of using only a single neural network framework is often ineffective, such as using a single LSTM or CNN. A single neural network framework focuses on different features of the data, CNN focuses on the lexical information of the data, is good at extracting the local features, and is able to capture the relevant features between the current word and the context. LSTM network focuses on the character information of the data, increases the structure of the gate, solves the problems of long-term dependence of RNN and gradient disappearance in backpropagation, and is better able to extract the historical features that are far away from the current word.CNN can not solve the problem of long-term dependence within the sequences, so BILSTM is introduced behind the CNN model, which solves the problem of long-term dependence within the input sequences. At the same time, the attention mechanism is introduced to focus the learning on entity words rather than non-entity words, which can reduce the influence of many noise words, solve the problem of insufficient feature extraction, and fully obtain the semantic features of the context associated with the important words, so that the feature extraction ability of the model is improved. The main role of the feature extraction layer is to use the dual-channel structure to extract the lexical information-based features of the text as well as the character information-based features through the two modules CNN+BILSTM+ATT channel and BILSTM+ATT channel, respectively. The two obtained features are spliced and fused in the feature fusion layer, and finally, the classification is done to get the output.

3.2.1 BILSTM+ATT Channels

The BILSTM+ATT channel consists of two layers.

(1) BILSTM layer: the BILSTM neural network structure is utilized to extract textual features from the output vector of the BERT model based on character information.

(2) ATTENTION layer: a weight vector is generated, and the feature vector obtained from the BILSTM layer is multiplied with this weight vector to obtain the long-distance dependencies existing in the data and further mine the information in the sentence. The structure is shown in Figure 3.

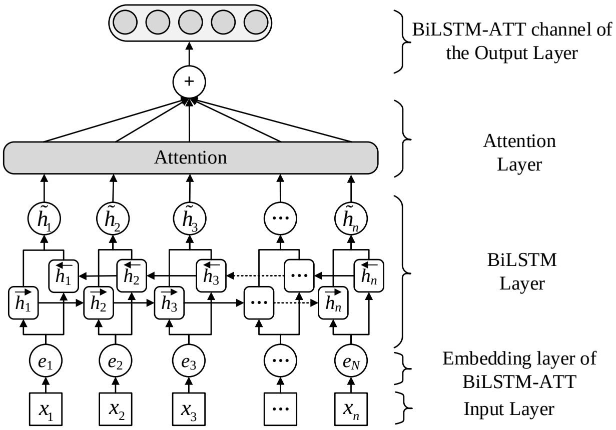

Figure 3: BILSTM+ATT channel structure diagram.

(1) BILSTM Layer:

LSTM is a variant of recurrent neural network RNN, which introduces the structure of a "gate" to control the passage of input information and memory information and solves the problems of long-term dependency of RNN and gradient disappearance in backpropagation, etc. LSTM mainly contains three gate structures, namely, the input gate to control input, the output gate to control output, and the forgetting gate to choose to discard unimportant information. The forgetting gate that chooses to discard unimportant information is the creative use of the three gate structures to control the passage of information through the gating mechanism to capture long-term dependencies. The joint action of the input gate and the forgetting gate determines that the LSTM is able to learn the long-term dependency, that what information is retained is controlled by the input gate, and that what information is forgotten is controlled by the forgetting gate. The memory unit manages and preserves information by learning the parameters of the three gates so that useful information is not forgotten in long sequences. The neuronal structure of the LSTM network at the t th moment is shown in Figure 4.

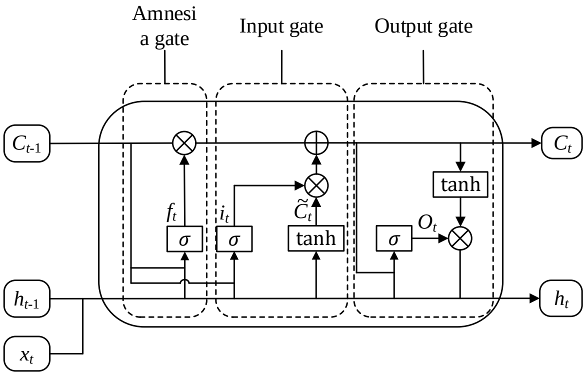

Figure 4: LSTM network structure diagram.

The LSTM network consists of the following components: the oblivion gate f_t , the input gate i_t , the output gate o_t , the cell state c_t and the hidden state h_t . c_{t-1}The cell state and h_{t-1} is the cell state and the hidden state of the previous moment ($t-1$ moment), respectively, and the specific formula of the forgetting gate f_t is as follows:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

Among them, σ is the activation function of $sigmoid$, W_f is the weight matrix of the oblivion gate, h_{t-1} denotes the output at the time of $t-1$, x_t denotes the input at the time of t , b_f is the bias vector of the oblivion gate and the state of the input gates i_t and t at the time of c_t is given in the following formulas:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$c_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{3}$$

Where W_i is the weight matrix of the input gate, b_i is the bias vector of the input gate, W_c is the weight matrix of the memory cell, b_c is the bias vector of the memory cell, and the memory cell c_t has the following specific formula:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{4}$$

Where, $\odot$ denotes the Hadamard product, and the output gates o_t and t momentary implicit layer states h_t . The specific formulas are as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \odot tanh(c_t) \tag{6}$$

where W_o is the weight matrix of the output gate and b_o is the bias vector of the output gate.

Single-layer LSTM performs feature extraction of sequences in chronological order; the forward LSTM network considers only historical information but not future information. The backward LSTM network, on the other hand, can consider future information. The unidirectional LSTM model can only output from front to back and does not repeatedly consider the contextual information. In this paper, we adopt a bidirectional LSTM model; the structure shown in Figure 4 BILSTM can utilize the contextual information to get the hidden feature representation in both the foreground and the background directions, which completely considers the information of the whole input sequence vector, and it can obtain more comprehensive semantic information compared with the unidirectional LSTM. Therefore, BILSTM is able to utilize all the history and future information fully, and the structure is shown in Figure 5.

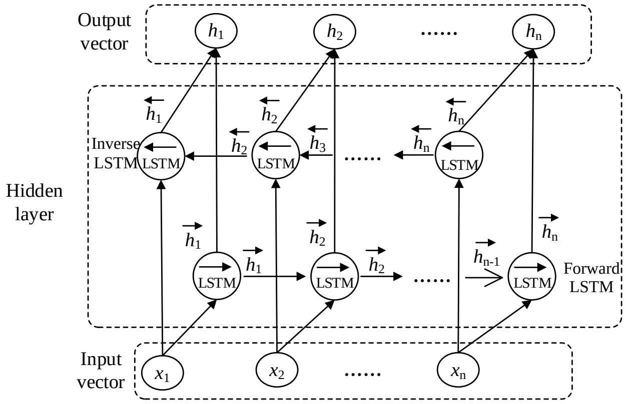

Figure 5: BILSTM network structure diagram.

The hidden state of BILSTM at the current moment (t moment) $\tilde{h}_t$ is determined by the input vector x_t at the current moment, the forward hidden state $\vec{h}_{t-1}$ and the reverse hidden state $\overleftarrow{h}_{t-1}$ at the previous moment ($t-1$ moment). i.e.:

$$\vec{h}_t = LSTM(x_t, \vec{h}_{t-1}) \tag{7}$$

$$\vec{h}_t = LSTM(x_t, \vec{h}_{t-1}) \tag{8}$$

$$\overleftarrow{h}_t = LSTM(x_t, \overleftarrow{h}_{t-1}) \tag{9}$$

$$\tilde{h}_t = [\vec{h}_t; \overleftarrow{h}_t] \tag{10}$$

Then, it is passed to the next layer. The text sequence vector $\tilde{X} = \{\tilde{x}_1, \tilde{x}_2 \cdots\cdots, \tilde{x}_n\}$ obtained from the word embedding layer after BERT modeling is input to get the final output vectors of the layer as $H = [\tilde{h}_1, \tilde{h}_2, \ldots \tilde{h}_n]$, $H \in \mathbb{R}^{n \times m}$.

(2) ATTENTION Layer:

The attention mechanism weights the vectors corresponding to the input sequence by emphasizing the importance of words and focuses the weights on the most important parts of the input sequence, i.e., focuses the learning on entity words rather than non-entity words, which reduces the influence of many noisy words and solves the problem of insufficient feature extraction, which is calculated as follows:

$$M = tanh(H) \tag{11}$$

$$\alpha = softmax(M \cdot W_\alpha) \tag{12}$$

$$U = \alpha^T \cdot H \tag{13}$$

Where W_α is the parameter vector and $softmax(G) = \frac{\exp(G)}{\sum_{j=1}^{c} \exp(G_j)}$, $G \in \mathbb{R}^c$, c are the dimensions of G .

The final output vector of the BILSTM+ATT channel is:

$$U^* = tanh(U) \tag{14}$$

3.2.2 CNN+BILSTM+ATT Channel

The CNN+BILSTM+ATT channel consists of three layers.

(1) CNN layer: fine-grained basis of BERT model output vectors to extract lexical information.

(2) BILSTM layer: the BILSTM neural network structure is utilized to extract textual features from the lexical information extracted based on CNN.

(3) ATTENTION layer: a weight vector is generated, and the feature vector obtained from the BILSTM layer is multiplied with this weight vector to obtain the long-distance dependencies existing in the data and further mine the information in the sentence. The structure is shown in Figure 6.

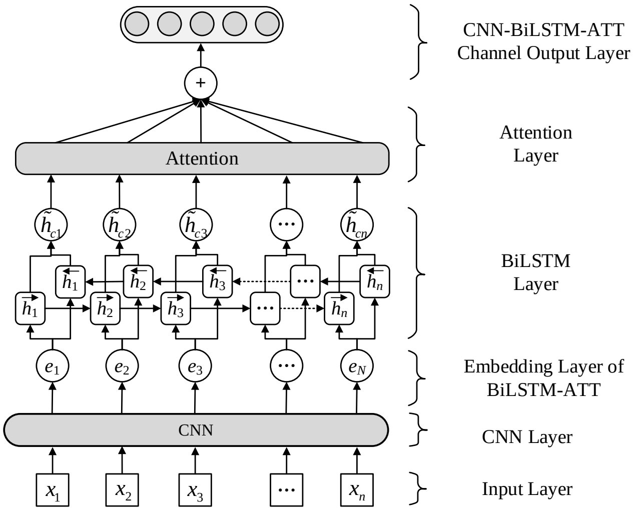

Figure 6: CNN+BILSTM+ATT channel structure diagram.

CNN is suitable for extracting local features and can represent the prefixes and suffixes of words and composition information, but it lacks attention to long-distance dependency information, while BILSTM pays more attention to temporal features and not enough attention to local features, so CNN combines with LSTM and lexical information is extracted by CNN on the fine-grained basis of the output vectors of the BERT model, and then LSTM does the lexical information-based Text feature extraction. The CNN layer is calculated as follows:

$$c_i = f(w \cdot x_{i:i+h-1} + b) \tag{15}$$

Where f is the activation function, w is the filter, h is the window size and b is the deviation term. $x_{1:n}$ Denote $[x_1, x_2, \ldots x_n]$, after the convolutional network, get the convolutional output $c = [c_1, c_2, \ldots c_{n-h+1}]$, $c \in \mathbb{R}^{n-h+1}$, after using Average pooling (Average pooling) to get the m dimensional features $h^{cov} \in \mathbb{R}^m$, then through the two-layer fully connected network, get the output vector of the convolutional neural network $H^{cnn} = [h_1^{cnn}, h_2^{cnn}, \ldots h_n^{cnn}]$, $H^{cnn} \in \mathbb{R}^d$, d is the size of the last hidden layer of the fully connected network. Next, similar to 2.2.1, the obtained H^{cnn} is input into the BILSTM network structure, based on the lexical information text feature extraction, to get the output vector R , and then R is input into the ATTENTION layer to get the final output vector R^* of the CNN+BILSTM+ATT channel.

3.3 Feature Fusion Layer

The output vectors of the BERT word embedding layer are processed by BILSTM+ATT channel based on character information and CNN+BILSTM+ATT channel based on vocabulary information to obtain the vector containing character features U^* and the vector containing vocabulary features R^* respectively. The two vectors are inputted into the feature fusion layer and then fused to obtain the dual-channel output vector, which is a fusion of character information and vocabulary information. The two vectors are inputted into the feature fusion layer and processed and fused to get the two-channel fusion output vector L which fuses the character information and vocabulary information:

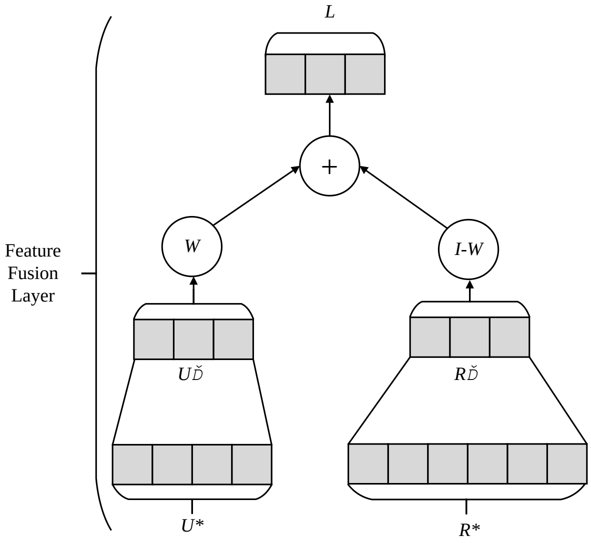

Figure 7: Structure of feature fusion layer.

The feature fusion layer first takes two input vectors of unequal dimensions and linearly transforms them into two vectors of the same dimension, U'、$R' \in \mathbb{R}^r$ that is:

$$U' = W_U \cdot U^{*T} \tag{16}$$

$$R' = W_R \cdot R^* \tag{17}$$

where $W_U \in \mathbb{R}^{r \times 2d^h}$ and $W_R \in \mathbb{R}^{r \times 2d^h}$ are both weight matrices and r is the number of relationship types.

The weight vector W is then used to fuse the transformed vector U'、R' to get the final output of the feature fusion layer L :

$$L = relu(W \odot R') + tanh((I - W) \odot U') \tag{18}$$

Among them are $I = [1,1,\cdots 1]^T$, $I, W, L \in \mathbb{R}^r$. The design of the feature fusion layer is derived from the Highway[39] network; there are two nonlinear transforms in the Highway network they are the transform gate $T(X \cdot W_T)$ and the feed gate $C(X \cdot W_C)$, and $\hat{O}$ is obtained by the following computation:

$$\hat{O} = P(X \cdot W_P) \odot T(X \cdot W_T) + X \odot (C(X \cdot W_C)) \tag{19}$$

where P、T、C is the activation function, usually $C(X, W_C) = I - T(X, W_T)$, so that

$$\hat{O} = P(X \cdot W_P) \odot T(X \cdot W_T) + X \odot (I - T(X \cdot W_T)) \tag{20}$$

The Highway network is required X、$\hat{O}$、$T(X \cdot W_T)$、$P(X \cdot W_L)$ to have the same dimensions. The essence of the Highway network is that one part of the input is processed in the same way as a traditional neural network, and the other part is passed straight through. In contrast to the Highway network, the feature fusion layer proposed in this chapter fuses inputs of two different dimensions. However, the fusion method is similar to the gating mechanism of the Highway network, and the feature fusion layer uses weight vectors W similar to the transform gate $T(X \cdot W_T)$ of the Highway network and $I - W$ similar to the feed gate $C(X, W_C) = I - T(X, W_T)$ of the Highway network to learn how to control the information flow of the output.

3.4 Output Layer

The relational extraction model is essentially a multi-categorization task, so the output layer uses the $softmax$ classifier for classification. $softmax$ It is a fully connected layer that serves to output the fused and spliced vector L and maps it to the $[0,1]$ interval, which is used to represent the probability scores of different categories. The specific formula is as follows:

$$P(y \mid S,\theta) = softmax(W^s \cdot L + d) \tag{21}$$

$$\hat{y} = argmax(P(y \mid S,\theta)) \tag{22}$$

Where θ are all the parameters that can be trained in the two-channel fusion model. $L \in \mathbb{R}^{d_L \times n}$ is the output of the feature fusion layer, $W^s \in \mathbb{R}^{K \times d_L}$ is the relationship classification parameter matrix, K is the number of categories, and d^L is the dimension of the feature fusion layer. Finally, the predicted result of entity relationship classification for the input text S is obtained $\hat{y}$.

In the multiclassification model training, the multiclassification cross-entropy function (cross-entropy loss) is used as the objective function, and the formula for the loss function is specified as follows:

$$Loss = -\frac{1}{K}\sum_{j=1}^{K} y_j^* \log\left(\hat{y}_j\right) \tag{23}$$

Where $\hat{y}$ is the predicted probability distribution of a sample vector in the sequence, and y^* is the true label of the sample vector. The smaller the loss rate in the loss function, the smaller the error between the predicted value and the true value, and the more accurate the judgment of the model. The optimization process of the model is the process of making the loss rate lower and reducing the error between the predicted value and the true value.

4 EXPERIMENTATION AND ANALYSIS

4.1 Experimental Data Preparation

4.1.1 Introduction to the Data Set

The experimental data of the article is the user comment data of the Sina automobile complaint platform, and the Octopus Collector tool is used to obtain more than 41,000 comment data, which are all unstructured text data. The data is exported and stored in the form of a table, which contains five parts: model, problem type, problem details, user ID, and time. Some of the raw data of user comments are shown in Figure 8. The main content of this paper is to extract the relationship after the automobile product-related entities obtained from user reviews, as shown in the table, so as to obtain more knowledge related to user needs and assist automobile enterprises in product innovation.

1	vehicle type	Type of problem	Details of the problem	user ID	timing
2	2023 Dongfeng Fengshen E70 500 Intellig	Engine/Motor (rattling)	Car bought back two months throttle rattling, the first time to go to the 4s store repa	Sina.com 21287595	2023/5/8 19:26
3	2022 Corsair 700km Long Range Rear Drive	Other (price changes)	I purchased BYD Seal xxx model in 2023.1.14, when the sales said BYD will not reduce th	Sina.com 21250749	2023/5/8 19:20
4	2021 Chang'an CS55 PLUS Blue Whale Editi	Transmission (oil leak)	Today, I went for maintenance and found that there was a transmission oil leak, less th	Sina.com 21287593	2023/5/8 19:16
5	2016 Vitara 1.4T Automatic 2WD Elite	Brake system (brake failure,	I received a recall notice from Yanji City, Jilin Province on March 13, 2023, advising	Sina.com 21287542	2023/5/8 19:16
6	2022 Corsair 700km Long Range Rear Drive	Brake system (rattles), body	BYD Seal front seat rust low speed brake rattle, this car experienced front badge paint	Sina.com 21287563	2023/5/8 19:11
7	2022 Audi Q7 55 TFSI quattro S line Pres	Bodywork accessories and elec	Import Audi Q7 generator failure aftermarket repair without parts, the vehicle broke do	Sina.com 21287560	2023/5/8 18:41
8	2022 KUSTO 270TGDi TOP	Body accessories and electric	Beijing Hyundai Kusatsu roof door and generator rattling, April 19, 2013 to pick up the	Sina.com 21284342	2023/5/8 18:34
9	2022 Yuan PLUS 510KM Flagship	Other (price changes)	BYD Yuan PLUS after picking up the car the manufacturer reduced the price for no reason	Sina.com 21287579	2023/5/8 18:30
10	Razor 2006 2.5V	Body accessories and electric	The dashboard is cracked, the oil coming out seriously affects driving, asked the manuf	Sina.com 21280424	2023/5/8 18:15
11	2022 Asiatic Dragon 2.5L Deluxe	Transmission (stutter)	Shift stuttering is obvious especially in the morning or cooler cars more serious 1 gea	Sina.com.cn 28417(	2023/5/8 18:08
12	2022 Yuan PLUS 510KM Flagship	Engine/Motor (won't start, po	I purchased a BYD Yuanplus pure electric car from Fujian 4s store on March 5, 2023, and	Sina.com 21287538	2023/5/8 17:52
13	2021 Audi Q5L 40 TFSI Luxury Dynamic	Body accessories and electric	Battery quality problems, the 4S store refused to replace, the first loss of power appe	Sina.com 21287554	2023/5/8 17:49
14	Razor 2007 2.5S Leather Sunroof Edition	Body accessories and electric	Dashboard appeared to deteriorate, to the 4S store to apply for replacement, the staff	Sina.com 21200356	2023/5/8 17:42
15	2021 Forester 1.5L Automatic Diamond Edi	Body accessories and electric	From the purchase of the car to now, has received three or four times Chongqing manufac	Sina.com 21287548	2023/5/8 17:35
16	2022 Corsair 550km Standard Range Rear I	Service attitude (rude attitu	After booking the car did not reach an agreement, refused to return the deposit, arroga	Sina.com 21287546	2023/5/8 17:18
17	2019 Geely Colorado 1.0T Automatic 200T	Body accessories and applianc	Swing arm rust, maintenance to not solve the problem, that can not be repaired, the att	Sina.com 21266661	2023/5/8 17:14
18	2021 BYD Song MAX Upgraded 1.5T Auto Lux	Engine/Motor (stalled, power	Vehicles in normal driving in the instrument suddenly black screen, and then the engine	Sina.com 21287530	2023/5/8 17:02
19	2022 Corsair 550km Standard Range Rear I	Other (price changes)	BYD Seal purchase after the manufacturer to change the price of the vehicle, non-genera	Sina.com 21279206	2023/5/8 17:01
20	2022 Changan UNI-K Hybrid Blue Whale iDI	Transmission (unable to accel	Spring Festival back home continuously ran more than 1300 kilometers, on the highway on	Sina.com 21251066	2023/5/8 17:00
21	2022 Corsair 700km Long Range Rear Drive	Other (price changes)	In order to support the domestic new energy, 22 years purchased the seal. But recently	Sina.com 2710883	2023/5/8 16:59
22	2021 Zero Run T03 400 Luxury Edition	Failure to deliver on promise	① You have also recovered the vehicle. And independently locked, vehicle information w	Sina.com 21121671	2023/5/8 16:55
23	2022 Peugeot 508L 400THP PureTech Harnes	Body accessories and electric	I Dongfeng Peugeot 508L purchased on May 23, 2022, purchased 2 days of engine fault lig	Sina.com 21230459	2023/5/8 16:48
24	2022 Corsair 550km Standard Range Rear I	Body accessories and applianc	The new model less than half a year price reduction of 30,000, out of the new quality u	Sina.com 21287527	2023/5/8 16:41
25	2022 Corsair 700km Long Range Rear Drive	Other (price changes)	The car was picked up on January 5, 2023, and by March 10 there were incentives that in	Sina.com 21287512	2023/5/8 16:33
26	2018 Audi A4L 2.0T Automatic 30th Annive	Engine/Motor (antifreeze leak	October 2022 - December vehicle cold start repeatedly prompted "maximum engine speed ov	Sina.com 21284287	2023/5/8 16:16
27	Crown 2005 3.0 Royal Saloon	Body accessories and electric	The dashboard of the FAW Toyota Crown is cracked and I hope the manufacturer fixes the	Sina.com 21286354	2023/5/8 16:13
28	Razor 2007 2.5V Sunroof	Body accessories and electric	The dashboard is cracked in many places, exposing the bottom, there is a quality proble	Sina.com 21287511	2023/5/8 16:11
29	2020 Explorer 2.3T Automatic EcoBoost 28	Body accessories and applianc	I in March 2021 in Baoding City, Hebei Province, Ford 4S store to buy Changan Ford 2020	Sina.com 21287509	2023/5/8 16:09
30	2021 KUSTO 380TGDi LUX Premium	Engine/motor (exhaust failure	Particle traps frequently clogged, each time is to run high speed plus regeneration, un	Sina.com 21287500	2023/5/8 16:01
31	2020 Mercedes-Benz GLE 350 4MATIC Style	Bodywork accessories and elec	The vehicle is a new Mercedes-Benz GLE, as soon as you hit the right steering, the wind	Sina.com 21281050	2023/5/8 15:49
32	2021 Link 06 1.5T Shero Pink Special Edi	Vehicle accessories and appli	The car was purchased and advertised with the clear indication that the car has an auto	Sina.com 21287496	2023/5/8 15:46
33	2018 Hennessey New Energy Smart Edition	Bodywork accessories and elec	The failure of the warranty period has been responded to (Exhibit 1: pre-maintenance st	Sina.com 21193180	2023/5/8 15:43
34	2023 Ridgeline PLUS 1.5T DCT Flagship	Engine/Motor (rattling), Tran	I am a retired military personnel, in line with the purpose of supporting the domestic,	Sina.com 21183589	2023/5/8 15:43
35	2021 Havoc Big Dog 1.5T Automatic Border	Body accessories and electric	Purchased in 2021, the first year to go to the 4s store to do maintenance, the results	Sina.com 21226430	2023/5/8 15:32

Figure 8: Example of raw data from the user comments section.

serial number	*Entity type*	*Entity Examples*
1	car brand	audi、red flag、mazda、byd、etc.
2	Car Model	Little Ant, Logo 408, Jetway Grand Sage, etc.
3	Automotive hardware	Engine, doors, transmission, dashboard, etc.
4	Hardware issues	Cracking, rusting, shaking, battery aging, etc.
5	automotive software	Navigation, car systems, operating systems, etc.
6	Software issues	Disconnection, lag, black screen, flashback, etc.
7	Objects of user dissatisfaction	4S stores, manufacturers, dealers, after-sales, customer service, etc.
8	Dissatisfaction with the performance of the target	Deduction of vehicle owners' rights and interests, perfunctory compensation, etc.
9	user needs	Free settlement, granting of extended warranties, compensation for gaps, etc.
10	user ID	Sina.com 21269020, etc.
11	Comment Time	2023/5/8 13:42, 2023/5/7 22:15, etc.

Table 1: Examples of entities resulting from the study.

4.1.2 Entity Relationship Labeling

Based on the 11 entity types obtained from previous studies, the article predefines 10 entity-to-entity relationships, as shown in the table below.

serial number	*Predefined relationship types*	*The entity type pair corresponding to the relationship*	*Relationship Examples*
1	Product Series	Car Model → Car Brand	BYD Song → BYD
2	software	Car hardware → Car model	Dashboard → Audi A6
3	Hardware problem performance	Automotive Hardware → Hardware Problems	Seat → Rust
4	hardware	Car Software → Car Models	Navigation → Red Flag H7
5	Software problem performance	Automotive Software → Software Issues	Car map → unresponsive
6	be part of	Object of dissatisfaction → Car model	4S→BYD Yuan
7	Reasons for dissatisfaction	Dissatisfied object → Dissatisfied object performance	Manufacturers → price cuts in disguise

8	demand (economics)	User ID → User Requirements	Sina 21269020 → Refund
9	commentaries	User ID → Car Model	Sina 21287469 → Mercedes-Benz GLC
10	Comment Point in Time	User ID → comment time	Sina.com 21287447→2023/5/8 14:19

Table 2: Predefined relationship types.

Due to the small amount of data crawled in this article, a semi-supervised data labeling strategy is used to label the limited data manually, and with the help of these labeled samples, supervised learning is carried out to label a large amount of unlabeled data, so as to obtain the final labeled data. In the article, among the 21,860 standard text data obtained after data processing, 2,000 items are randomly selected for manual data annotation, and the text annotation tool used is the Doccano text data annotation platform. Some of the annotation examples are shown in Figure 9. Doccano can easily and efficiently carry out a lot of natural language processing tasks, such as named entity recognition, sequence annotation, and text classification tasks. Doccano can easily and efficiently perform many natural language processing tasks, such as named entity recognition, sequence labeling, and text classification.

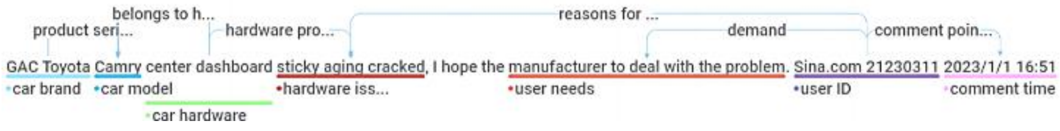

Figure 9: Example of some labeling.

This annotation platform can export the labeled data to Jason format. The division ratio of the training set, validation set, and test set is set to 8:1:1. Jason's text data format is as follows:
{"id":18255, "text": "GAC Toyota Camry center dashboard sticky aging cracked, I hope the manufacturer to deal with the problem. Sina.com 21230311 2023\/1\/1 16:51", "relations":[{"id":35862, "from_id":24543, "to_id":24544, "type": "product series"},{"id":35863, "from_id":24545, "to_id":24544, "type": "belongs to hardware"},{"id":35864, "from_id":24545, "to_id":24546, "type": "hardware problem performance"},{"id":35865, "from_id":24548, "to_id":24546, "type": "reasons for dissatisfaction"},{"id":35867, "from_id":24548, "to_id":24547, "type": "demand"},{"id":35868, "from_id":24548, "to_id":24549, "type": "comment point in time"}]}.

The relationship between the hardware entity "center dashboard" corresponding to fields 7 to 12 in the text and the hardware problem entity "reflective cracking" corresponding to fields 12 to 18 in the text can be obtained as "hardware problem manifestation." Since the output text data is too long and contains a lot of redundant information, and at the same time, too long text will affect the recognition of the BERT model, and we cannot use Jason's text data output by Doccano, so we use the Python tool to intercept the output text data according to the position of the two entities that have a relationship with each other, and the purpose of this step is to remove the redundant text and shorten the text length to prevent it from exceeding 512 characters. The purpose of this step is to remove redundant text and shorten the length of the text to prevent the loss of information after BERT when it exceeds 512 characters. After the interception process, we can get a shorter text containing the head entity-relationship-tail entity ternary, for example {"en1_type": "Automobile hardware," "en1_val": "Throttle," "en1_start": 53, "en1_end": 55, "en2_type": "Hardware problem," "en2_val": "Rattle," " en2_start": 55, "en2_end": 57, "rel_type": "Hardware problem performance," "text": "Dongfeng Fengshen E70 accelerates or releases the throttle door rattling obviously}, which facilitates the training of the subsequent model and improves the accuracy of the relational extraction model.

4.2 Experimental Design

4.2.1 Experimental Environment

All experiments in this paper were conducted on NVIDIA NVIDIA GeForce GTX 4060 GPUs using the PyTorch open-source framework for network training as shown in Table 3 with the following detailed hardware and software information.

Name of the experimental environment	*text*
CPU Model	13th Gen Intel(R) Core(TM) i9-13900HX
GPU Model	NVIDIA GeForce GTX 4060 16GB
operating system	Windows 11
random access memory (RAM)	64GB
programming language	Python 3.9
Deep Learning Framework	Pytorch 1.7.1

Table 1: Experimental environment setting.

4.2.2 Relational Extraction Model Training

In this paper, we adopt the Python programming language and use the deep learning PyTorch framework to construct a named entity recognition model and entity relationship extraction model. We fully use the training set, validation set, and test set for model training, parameter optimization, and validation inference, respectively.

The word embedding layer of the named entity recognition model is chosen to be the BERTBASE model, which has the number of attention heads of 12, the dimension of the hidden layer of 768, and the number of Transformer block layers of 12. In the text length setting, since the maximum length of the BERT input is 512 characters, the long text with a length of more than 512 is processed by segmentation and is insufficiently complementary. The batch size is set to 8, and the batch size is set to 12. The batch size is set to 8, and the model is trained for 40 iteration cycles. The early stop parameter is 5, i.e., the training is terminated when the loss of 5 consecutive batch validation sets no longer decreases. The CNN Dropout is 0.4, and a Bi-LSTM Dropout layer with a ratio of 0.2 is introduced into the fully connected layer; the batch size is set to 16, Adam is used to optimize the model parameters, and the specific parameter settings are shown in Table 3.4. In terms of training parameters, through repeated tuning and parameter adjustment, we finally set the initial learning rate of BERT to 6e-5, and the initial learning rate of the model to 1e-4, and the specific hyperparameter settings are shown in Table 4.

hyper parameterization	*hyperparameter value*
dimension of a word vector	768
Transformer Number of hidden layers	12
Transformer Hidden Layer Dimension	768
attention span	12

Bi-LSTM hidden layer dimension	512
Bi-LSTM Dropout	0.2
CNN Dropout	0.4
batch_size (sample size per batch)	16
epoch (number of model training iterations)	30
optimizer	Adam

Table 2: Hyper Parameter Setting.

4.3 Experimental Evaluation Indicators

In order to evaluate the performance of the proposed model in this paper, three evaluation metrics commonly used in sequence annotation tasks are used: precision, recall, and F1 value. Precision indicates the proportion of actual positive cases among the samples predicted by the model as positive cases. Recall indicates the proportion of correctly predicted positive cases among all actual positive cases.F1 value is a comprehensive evaluation of the performance of the classification model, which takes into account both Precision and Recall and is used to measure the balance of the model in the positive and negative cases in the prediction. The formula is specified below:

$$P = \frac{TP}{TP + FP} \tag{24}$$

$$R = \frac{TP}{TP + FN} \tag{25}$$

$$F_1 = \frac{2PR}{P + R} \tag{26}$$

Where TP (True Positive) stands for True Example, which represents the number of samples that the model correctly predicts as positive examples. fp (False Positive) stands for False Positive, which represents the number of samples of negative examples that the model incorrectly predicts as positive examples. fn (False Negative) stands for False Negative, which represents the number of samples of positive examples that the model incorrectly predicts as negative examples.

4.4 Analysis of Experimental Results

In order to validate the effectiveness of the proposed two-channel fusion BERT+ (CNN+BILSTM+ATT, BILSTM+ATT)-based entity-relationship extraction model, experimental datasets constructed using automobile user review texts as well as entities obtained from previous studies are used for comparison experiments. The comparison models include the current BERT+ CNN+BILSTM+ATT model [5], BERT +CNN model, BERT+ BILSTM model, BERT+ CNN+BILSTM model, BERT+ BILSTM+ATT model, which has a better effect on the recognition of the domain of the currently named entities, and the effect of each model of the comparison experiment is shown in Table 5. A comparison of the intuitive experimental results on each evaluation index is shown in Figure 10.

number	*mold*	*P*	*R*	*F1*
1	BERT +CNN	83.26	82.17	82.71

2	BERT+ BILSTM	83.22	84.63	83.91
3	BERT+ CNN+BILSTM	86.59	88.31	87.44
4	BERT+ BILSTM+ATT	86.72	84.19	84.20
5	BERT+ CNN+BILSTM+ATT	88.43	90.26	89.34
6	model of this paper	92.35	92.79	92.57

Table 3: Comparison of overall recognition results of each model (%).

Through the experimental results, comparing Model 1 and Model 2, it can be found that the BILSTM model has a slightly lower accuracy than the CNN model, but the recall rate is higher. The overall relationship extraction effect is higher than that of the CNN model, the reason is that the text sequences of the text inputs are all long text data. The BILSTM model is more capable of capturing the sequence-dependent information, and is able to obtain the contextual feature representation of the long text. In contrast, the CNN model focuses on the lexical information of the data, while it is good at extracting local features. It can capture the relevant features between the current word and the context but cannot solve the sequence's internal Long-term dependency problem. Comparing Model 3 with Models 1 and 2, it can be seen that the CNN+BILSTM model outperforms the CNN+BILSTM model in all the relational extraction metrics than the separate.The CNN model and BILSTM model. BILSTM cannot capture important local feature information. Still, the CNN model can make up for this shortcoming of the BILSTM model. In contrast, the introduction of BILSTM behind the CNN model solves the problem of long-term dependence within the input sequences and, at the same time, combines the local feature extraction capability of the CNN model and the global feature extraction capability of the BILSTM model to improve the relational extraction capability of the model. The feature extraction ability of the CNN model and the global feature extraction ability of the BILSTM model improve the relationship extraction ability of the model. Comparing models 4 and 5 with 2 and 3, it can be seen that all the evaluation indexes of the models are improved after adding the attention mechanism. Because the attention mechanism will focus the learning on entity words rather than non-entity words, which can reduce the influence of many noise words, solve the problem of insufficient feature extraction, fully obtain the semantic features of the context associated with important words, and improve the training effect of the model. Comparing model 6 and models 4 and 5, it can be seen that after using the innovative dual-channel relationship extraction model in this paper, all the indexes of the model are significantly improved, and the model has the best relationship extraction effect. The CNN+BILSTM+ATT model can adequately extract the lexical information features of the input text sequences, and BILSTM+ATT can adequately extract the character information features of the input text sequences, and the two features are fused to obtain the fused lexical information features of the input text sequences. These two features are fused to obtain the fusion vocabulary and character information extraction features, which greatly enriches the semantic features of the text, improves the semantic learning ability of the model, and demonstrates the effectiveness of this paper's model in carrying out the automobile user demand entity relationship extraction. As can be seen from Table 5, the entity recognition F1 value of the model proposed in this paper is 92.57%, with the best recognition effect, which exceeds the current mainstream named entity recognition model as far as the data set of this paper is concerned, and it has certain reference value in carrying out the relationship extraction of automobile user requirements.

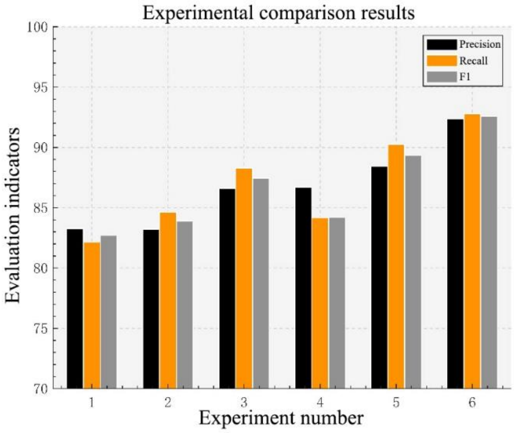

Figure 10: Comparison of the overall recognition effect of the model.

5 CONCLUSIONS

Aiming at the shortcomings of the existing research on relational extraction in the automotive domain, none of the existing methods can solve the problem of word polysemy well, and they do not have a good recognition effect when facing the existence of complex interrelationships among multiple entities, a dual-channel BERT+(CNN+BILSTM+ATT, BILSTM+ATT)-based relational extraction model for automotive user requirements is proposed. In the word embedding layer, the BERT model is used to obtain the character-level dynamic vectors of the input text sequence, which solves the problem of multiple meanings of the word; in the feature extraction layer, the feature extraction of the input text sequence is carried out through the dual-channel structure, and in the BILSTM+ATT channel, BILSTM is used to extract the global contextual semantic features of the text based on the character information and the attention mechanism is used to obtain the data with the existence of the long-distance dependencies to further mine the information in the sentences. In the CNN+BILSTM+ATT channel, the lexical information is extracted using the CNN model on the fine-grained basis of the output vectors of the BERT model, and the textual features of the lexical information extracted on the basis of the CNN are extracted using the structure of the BILSTM neural network, and finally, the long-distance dependencies existing in the data are obtained through the attention mechanism to further excavate the information in the sentences; in the feature fusion layer, the, Unlike the existing method of directly splicing the outputs of the two channels, the model uses a trainable weight vector in the feature fusion layer to determine the ratio of the vectors of the two channels' outputs, so that it can be trained to get the best ratio, thus maximizing the advantages of the two neural networks to achieve a better effect of relationship extraction. The final result is obtained by using the *softmax* classifier for classification at the output layer. Experiments show that the F1 value of the proposed model in this paper reaches 92.57%, which is higher than other models, proving the effectiveness of the proposed model in this paper.

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